TRAFFIC DEMAND ESTIMATION MODEL FOR ACTUAL ROAD NETWORK BY OBSERVED LINK FLOWS REGARDING GENERATION TRIPS ONLY AS UNKNOWNS

SUBTHEME (A): MAN AND HIS TRANSPORT BEHAVIOUR

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1. INTRODUCTION

The sequential step method has been most commonly used so far as a conventional traffic demand estimation model. Despite that it requires in general a great amount of man power, cost and time in the collection and the processing of the data, however, it seems difficult to apply the traffic demands estimated by this model to traffic control or regulation systems on a real life road network. This is because spatial aggregation as an areal unit of generation and attraction trips does not necessarily match with the real life network for convenience of collection of the existing socioeconomic data and for a simplicity of computation works. It has been also pointed out that the sequential step model has a deficiency of logical inconsistency that there is little or no feedback among the estimation processes.

As a result of the growing dissatisfaction with the conventional procedures, some new concepts of travel forecasting model have been proposed and developed, which is aiming to simplify and economize the data processing works and at the same time to provide high accuracy in the estimates. Current research works on model development based on the new concepts could be categorized into the following two main streams. One is based on behavioural travel demand model or disaggregate model, and the other is on model by observed link flows. Although there remain some problems for practical use, it is expected that the new models might hold the potential to replace the conventional travel forecasting procedure.

This paper will concentrate upon only the model by observed traffic volumes on links. With respect to this type of model, Willumsen (1981) identified the following three approaches. The first approach consists of assuming that trip making behaviour can be explained by a gravity model. The second approach uses mathematical programming techniques associated to equilibrium assignment problems. The third approach relies on entropy and information theory considerations. However, these approaches are not necessarily exclusive ones but sometimes used in a joint manner in the model building.

The model discussed in this paper is based on a gravity model approach. The previous works by this approach can be classified into some groups according to the amount of additional information on traffic behaviour. One subgroup includes models in which generation and attraction trips (or their respective socioeconomic indices) of each zone, deterrence (or cost) function and link flow proportions (or route choice probabilities) of each OD pair are assumed to be known (Low, 1973. Overgaard, 1974(OECD Report). Robillard, 1974. Carey.et al, 1981). The other subgroup consists of models based on the assumption that generation and attraction trips (or their respective socioeconomic indices) of each zone and deterrence (or cost) function of each OD pair are known, in which traffic assignment procedure is incorporated (Holm.et al, 1976. May.et al, 1981). In the above models, the gravity model parameters are caliblated to produce an OD matrix consistent with observed link flows by using regression analysis or maximum likelyhood method.

Now this paper provides a model in which generation trips from each node are treated as unknowns for given sets of link flow proportions and trip interchange factors of OD pairs. At this time, the trip interchange factor consists of deterrence function and adjusting factor to agree with an existing or an earlier OD pattern. In this model it is premised that traffic flows are observed on all links, and therefore attraction trips of each node are not necessary to be used, which can be expressed respectively by a function of generation trips of the nodes. An OD matrix can be estimated through an iterative calculation by choosing a set of generation trips of nodes giving a best goodness of fit between calculated and observed link flows. But this model has defects that a unique OD matrix can not be produced for some types of network and of route choice behaviour, and that the convergence can not necessarily be completed in the iterative calculation. It could be possible to consider some countermeasures to overcome the weak points, but they are a little cumbersome for practical application.

Thus the model is modified in such a way that a closeness of fit between calculated and observed generation trip proportions among nodes should be attained in addition to a goodness of fit on link flows. This model can not only overcome the problems of the previous model but also produce more rapid convergence in the iterative calculation. Although traffic movements change with various conditions, the given values in the models are assumed as constants. Nevertheless, in some occasions link flows are observed at a different period from that of OD traffic survey and/or route choice survey. Furthermore, a simplification of network representation cause errors in link flows. From this viewpoint, the sensitivity analyses by simulation are performed to examine the influences by errors in the given data on the prediction errors in the results.

By the way the words "flow" and "volume", and "zone" and "node" will be interchangeably used in this paper.

2. BASIC IDEA

A road network of Fig.1 is an example illustrating nodes for trip generation and attraction, traffic observing points and zone boundary lines in an application of the model. The purpose of the model is to estimate an OD matrix from traffic counts on the links. In this case, however, generation and attraction trips at edge nodes on the study network are provided respectively by link flows entering into and leaving from the network.

Suppose that OD travel volumes could be shown in terms of a gravity model as below.

$$T_{ij} = \alpha_i A_i \beta_j B_j R_{ij} \;, \tag{1}$$

where A_i is the number of trips originating from zone i, B_j is the number of trips terminating to zone j, R_{ij} is a trip interchange factor, and α_i and β_j are balancing factors satisfying trip end constraints written by eqs.(2) and (3).

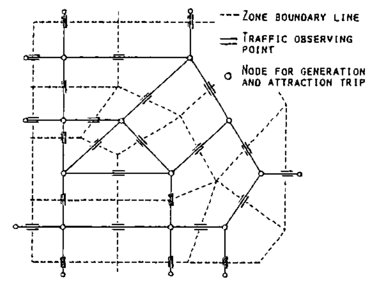


Fig.1 An example of network.

$$\Sigma_j \, T_{ij} = A_i \;. \tag{2}$$

$$\Sigma_i \, T_{ij} = B_j \;. \tag{3}$$

It must be noted here that a trip interchange factor represents a measure of spacial separation calibrated by the adjusting factor to agree with an existing or an ealier OD pattern.

Now there exists a relationship that a difference between generation and attraction trips at a zone is equal to a difference between the totals of outward and inward link flows observed at the zone boundary line. That is,

$$A_i - B_i = \Sigma_k \, (RX_{ik} - RX_{ki}) \;, \tag{4}$$

where RX_{ik} is an observed or a real traffic flow on link from node i to node k. As the model is based on the assumption that traffic volumes are observed on every link in the network, the value of the righthand side of eq.(4) is definite, or ΔD_i. It follows therefore that an attraction trips B_i is determined by a generation trips A_i. That is,

$$B_i = A_i - \Delta D_i \;. \tag{5}$$

Thus substituting eq.(5) into eq.(1) leads to eq.(6).

$$T_{ij} = \alpha_i A_i \beta_j (A_j - \Delta D_j) R_{ij} \;. \tag{6}$$

From this, we can derive a calculated or an estimated flow on link mn, or X_{mn} as shown in eq.(7).

$$X_{mn} = \Sigma_{ij \in mn} \, [\alpha_i A_i \beta_j (A_j - \Delta D_j) R_{ij}] P_{ij}^{mn} \;, \tag{7}$$

where P_{ij}^{mn} is a probability of using link mn by ODij. Hence, a link flow is found to be a function of three variables, that is, A_i, R_{ij} and P_{ij}^{mn}.

Consequently, a traffic demand estimation by link flows could be performed by selecting the sets of the values of A_i, R_{ij} and P_{ij}^{mn} minimizing the differences between observed and estimated link flows. If all the sets of them should be unknown, however, an OD matrix consistent with link flows would not be unique, because the number of the unknowns in general exceeds that of the links. In order to reduce this underspecified problem, it would be necessary to provide externally some of the sets of the variables by using extra information on trip making. Then, the models by observed link flows can be classified into four types as shown in Table 1 according to which set (s) of variables is(are) externally given as constants.

Table 1. A classification of models by link flows.

Model type	Known flows	Flows to be estimated
1	R_{ij}, P_{ij}^{mn}	A_i
2	A_i, R_{ij}	P_{ij}^{mn}
3	R_{ij}	A_i, P_{ij}^{mn}
4	A_i	T_{ij}, P_{ij}^{mn}

The model type 1 is that a set of A_i only is regarded as unknowns (Iida, 1978). The model type 2 is identical with a traffic assignment problem in accord with observed link flows, because it implies that predetermination of A_i and R_{ij} provides an OD matrix (Iida, 1979). The model type 3 is equivalent to a combined trip distribution-assignment problem under the restriction of agreement with observed link flows (Iida. et al, 1982). The model type 4 is a unique model distinguished from the above model types on the basis of a gravity model approach, in which a set of A_i is provided from turning movements at nodes (Iida, 1978). Which model type should be used for practical application depends mainly upon the purpose of the estimation and the availability of the data. However, the discussion here is limited to the model type 1.

3. MODEL BY LINK FLOWS ONLY

(1) Algorithm

Let us suppose that trip interchange factors and link flow proportions by OD pairs are assumed to be known. In this model the trip interchange factor is given by eq.(8).

$$R_{ij} = K_{ij}F(c_{ij}) \quad , \tag{8}$$

where K_{ij} is an adjusting factor peculiar to ODij to agree with an existing or an earlier OD pattern, $F(c_{ij})$ is a deterrence function between ODij, and c_{ij} is a travel time or cost between ODij. This trip interchange factor could be provided by eq.(9).

$$R_{ij} = t_{ij}/(a_i b_j) \quad , \tag{9}$$

where t_{ij} is the number of OD trips from node i to node j, a_i is the number of generation trips at node i and b_j is the number of attraction trips at node j at an earier period or by a sample survey.

On the other hand, in order to give a link flow proportion by an OD pair, or P_{ij}^{mn}, one can utilize a theory or a survey on route choice behaviour.

Then an OD matrix can be produced by selecting a set of A_i minimizing the sum of squares of the relative differences between calculated and observed link flows. That is,

$$Z = \Sigma_{mn}\{(RX_{mn} - X_{mn})/RX_{mn}\}^2 \longrightarrow \text{Min.} \qquad (10)$$

where RX_{mn} and X_{mn} are observed and calculated flows on link mn respectively.

The algorithm for this solution can be performed through an iterative calculation shown in Fig.2, in which the calibration of A_i by using eq.(11) is continued until a closeness of fit shown by eq.(12) is satisfied.

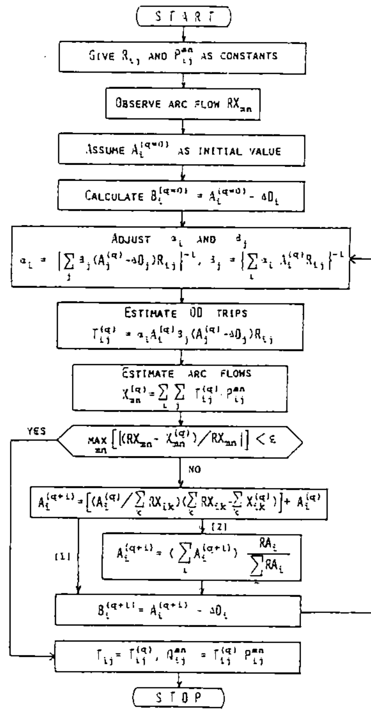
$$A_i^{(q+1)} = [(A_i^{(q)}/\Sigma_k RX_{ik})\cdot(\Sigma_k RX_{ik} - \Sigma_k X_{ik}^{(q)})] + A_i^{(q)} . \qquad (11)$$

$$\underset{mn}{\text{Max}} \left[\left| (RX_{mn} - X_{mn}^{(q)})/RX_{mn} \right| \right] \leq \varepsilon . \qquad (12)$$

In order to give efficient and stable convergence in the iterative calculation, eq.(11) is not theoretically but experimentally derived.

(2) Sensitivity analysis

It is interesting and important to investigate influences by variation in R_{ij} and P_{ij}^{mn} on the accuracy in the estimates, because the given values of R_{ij} and P_{ij}^{mn} at an earlier period are sometimes different from those at a forecast period. Also they are not necessarily synchronized with the observed link flow data. Hence, let us examine this by means of simulations.



[1]: for the initial model.
[2]: for the modified model.

Fig.2 Algorithm of the model.

Consider here a variation in an OD pattern as a variation in R_{ij} for convenience of the simulation, because R_{ij} can be regarded approximately as a factor representing the OD pattern if there is no significant change in generation and attraction trip patterns.

Assuming that a relative error in trips of ODij, or y_{ij}, is subject to a normal distribution with a mean value of μ_T (= 0) and a variance σ_T^2, or N(μ_T, σ_T^2) leads to eq.(13)

$$RT_{ij} = T_{ij}^{*}(1.0 - \sigma_T z_{ij}) \qquad (13)$$

$$z_{ij} = (y_{ij} - \mu_T)/\sigma_T \qquad (14)$$

where RT_{ij} is a real or a true value of OD trips from node i to node j at a forecast period and T^*_{ij} is that at an earlier period, but the total of RT_{ij} is adjusted so as to agree with the total of T^*_{ij}. Then giving random normal deviates to the set of z_{ij}, we can produce an OD matrix whose OD pattern has a variance of σ^2_T for the earlier one.

In a similar way, it is possible to provide RP^{mn}_{ij} as a real value of probability of ODij using link mn at a forecast period with a variance of σ^2_P for the earlier P^{*mn}_{ij}. In this simulation, however, RP^{mn}_{ij} is made by giving a variance in branching probabilities of flows at each node under the restriction of flow conservation relationships.

It must be noted here that, as large values of σ_T and σ_P violate that RT_{ij} and RP^{mn}_{ij} must be non-negative, the variations in σ_T and σ_P are limited within 0.5 and 0.35 respectively. Thus the sensitivity analyses on prediction errors are performed by varing the set of values of RX_{mn}, represented by eq.(15).

$$RX_{mn} = \Sigma_{ij\epsilon mn} (RT_{ij} RP^{mn}_{ij}) \quad . \tag{15}$$

Although there are a variety of measures of prediction error, the weighted root mean square relative error is used in this paper, because it can be considered from a viewpoint of traffic engineering that the accuracy in heavy traffic volumes is in general more important than that in light ones. For example, a prediction error in OD trips, or δ_{OD}, is shown by eq.(16).

$$\delta_{OD} = [(1/RT)\ \Sigma_{ij}\ RT_{ij}\{(T_{ij} - RT_{ij})/RT_{ij}\}^2]^{1/2} \tag{16}$$

where $RT = \Sigma_{ij}\ RT_{ij}$.

Let us suppose a road network in Fig.3 and an artificial OD matrix T^*_{ij} as an earlier data in the upper row in Table 2. But a set of P^{*mn}_{ij} is omitted here. When $\sigma_T = 0$ and $\sigma_P = 0$, the model produces the estimates of the OD trips shown in the lower row in Table 2, in which it is assumed that $\varepsilon = 10^{-3}$. It follows that the prediction error in OD trips is 2.4% and that in generation trips is 2.1%. Needless to say, the prediction error depends upon an exactness on goodness of fit on link flows. One could ascertain that a further continuation of the iteration would yield an OD matrix exactly equal to the given one.

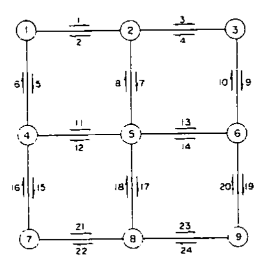


Fig.3 Road network for simulation.

When σ_T and σ_P are changed, the prediction errors in OD trips, in traffic flows on links by OD pairs and in generation (or attraction) trips are shown respectively in Fig.4, Fig.5 and Fig.6. Let us see first the prediction errors in OD trips. In general, it can be found that the prediction error grows with the increase in σ_T and σ_P. But what must be noticed here is that the influence by the variation in σ_P on the prediction error is far

Table 2 Given and estimated matrices.

O \ D	1	2	3	4	5	6	7	8	9	Total
1	—	530 538	470 460	590 597	410 383	300 304	370 363	320 324	260 255	3250 3223
2	500 508	—	560 569	383 399	600 581	370 389	290 295	400 420	330 336	3430 3497
3	420 411	590 598	—	330 334	360 335	540 546	240 235	340 344	390 382	3210 3185
4	550 557	390 409	320 324	—	500 482	480 502	480 486	380 397	300 304	3400 3462
5	420 392	490 474	380 354	520 502	—	540 521	390 364	460 443	390 365	3590 3414
6	290 294	400 419	550 557	410 429	530 511	—	350 355	400 418	570 578	3500 3560
7	380 373	300 305	240 235	500 507	390 364	310 314	—	520 527	470 462	3110 3085
8	320 323	440 460	360 364	440 459	500 481	420 438	600 607	—	540 546	3620 3679
9	300 295	290 295	430 422	350 355	370 346	540 547	480 471	540 547	—	3300 3278
Total	3180 3153	3430 3497	3310 3285	3520 3582	3660 3484	3500 3560	3200 3175	3360 3419	3250 3228	30410 30381

Upper: given. Lower: estimated.

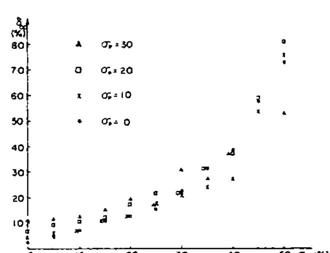


Fig.4 Prediction errors in OD trips.

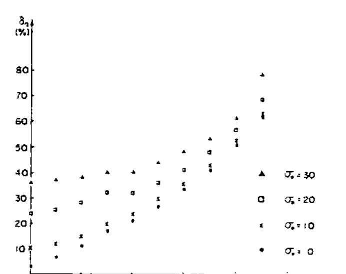


Fig.5 Prediction errors in link flow by OD pair.

less than that by the variation in σ_T as seen in Fig.4. For example, when σ_T = 0.30 and σ_P = 0, δ_{OD} is 0.23. Oppositely, when σ_T = 0 and σ_P = 0.30, we get δ_{OD} = 0.11. Consequently, how to give an accurate or a reliable value of R_{ij} seems to be more important subject in this model. It is also necessary to pay attention that,

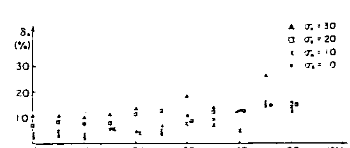


Fig.6 Prediction errors in generation trips.

when σ_T exceeds 0.4, δ_{OD} shows a sharp increase. In regard to link flows by OD pairs, it can be seen that, when σ_T is small, the prediction error, or δ_Q, is clearly affected by σ_P, but as σ_T increases, the influence by σ_P becomes less. With generation trips, it is found that the prediction error, written by δ_A, shows only a slight change for the variations in σ_T and σ_P as seen in Table 3. Finally, the accuracy in the estimates of the total OD trips is always markedly high except for the worst case that σ_T = 0.50

Table 3 Prediction errors in total OD trips.

σ_P \ σ_T	.00	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50
.00	.00	.00	.00	.01	.01	.01	.02	.00	.02	.04	.09
.05	.00	.00	.01	.01	.01	.01	.01	.02	.02	.02	.07
.10	.00	.00	.01	.01	.01	.01	.01	.02	.02	.02	.09
.15	.00	.00	.01	.00	.01	.01	.02	.00	.02	..04	.09
.20	.00	.00	.01	.01	.03	.01	.02	.00	.01	.04	.09
.25	.00	.00	.00	.01	.01	.01	.02	.03	.01	.02	.03
.30	.01	.00	.00	.00	.01	.01	.03	.02	.00	.04	.04
.35	.00	.00	.01	.02	.01	.00	.03	.03	.00	.02	.08

Through the above simulations, it has been clarified that the variation in σ_P does not give a vital affection on prediction errors for each kind of traffic demand when σ_T is large. Concerning this, we can consider the following reasons. The first is that, although the variation in σ_T has a direct effect on the estimates of OD trips, the effect by the variation in σ_P is dispersed over a number of routes used between OD pairs. The second is that, as the link flows are accumulated for OD pairs on the respective links, the effect by the variation in σ_P would be cancelled on the links. It might be concluded from this that even a rough value of P_{ij}^{mn} could be used for an estimation of OD trips.

(3) Weak points of the model

For some particular types of road network, such as a linear network and a one way loop network, the model does not produce a unique OD matrix. In the case of a linear network it can be proved as follows. Suppose a linear network with three nodes as shown in Fig.7 in which the relationship of eq.(17) should be hold.

$$\left.\begin{aligned} RX_{12} &= T_{12} + T_{13} = A_1 \\ RX_{23} &= T_{13} + T_{23} = B_3 \\ RX_{21} &= T_{21} + T_{31} = B_1 \\ RX_{32} &= T_{31} + T_{32} = A_3 \end{aligned}\right\} \quad (17)$$

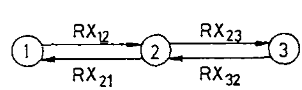


Fig.7 A linear network with three nodes.

These relationships mean that the generation and the attraction trips at the edge nodes, or node 1 and node 3, are given by the link flows, and at the same time the observed flows are equal to the estimated ones. But the generation and attraction trips at node 2 are not unique, because we can easily determine any sets of values of A_2 and B_2 satisfying a relationship shown by eq. (18), which is derived from eq.(17).

$$A_2 - B_2 = (RX_{21} + RX_{23}) - (RX_{12} + RX_{32})$$
$$= (B_1 + B_3) - (A_1 + A_3) = \text{constant.} \qquad (18)$$

With this type of network, therefore, it is proved that the model based on a gravity model represented by eq.(6) could produce a variety of OD matrix consistent with observed link flows even if sets of R_{ij} and P_{ij}^{mn} were known. When the scale of the linear network becomes larger, this can be verified inductively in the same way.

With a one way loop network, for example, as shown in Fig.8, it seems difficult to prove mathematically this. However it has been confirmed that a different set of initial values of A_i provides a different OD matrix (Nakajima, 1978). In addition, a uniqueness of OD matrix is considered to depend upon a set of route choice of each OD pair.

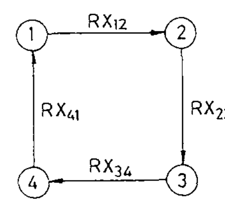


Fig.8 A one way loop network.

On account of this problem, it should be recommended in the case of practical application of the model to perform a test run in advance in order to know whether there exists a unique set of A_i or not. If the set (or the subset) of A_i is found to be non-unique, the following two methods could be employed for determination of the unique values. The first is a method to provide the values externally to them, and the second is a method making use of an information on generation trip proportions among nodes (or generation trip pattern) as shown later.

There is one more problem in this model that the convergence in the iterative calculation for correction of A_i is not necessarily completed, because the closeness of fit between the observed and the calculated flows is examined not on the respective but on the total link flows emerging from each node, and therefore, it sometimes occurs that the positive errors on some links are cancelled by negative errors on the other links. But it has been observed that temporal and random perturbations of flow branching probabilities at each node produce an effective improvement in the convergence.

4. MODEL BY LINK FLOWS AND GENERATION TRIP PATTERN

(1) Algorithm

As stated above, the estimation model by link flows only will, on some occasions, produce a non-unique OD matrix. In order to overcome this problem, one can utilize an information on generation trip proportions among nodes (or generation trip pattern). An estimation by this modified model is conducted by minimizing the differences between given and calculated proportions of generation trips among nodes, together with a goodness of fit on link flows, which is shown in eq.(19),

$$Z = \Sigma_{mn} \{(RX_{mn} - X_{mn})/RX_{mn}\}^2 + \Sigma_i (a_i/a - A_i/A)^2 \longrightarrow \text{Min.} \qquad (19)$$

where a_i is the number of generation trips at node i by a previous data, and $a = \Sigma_i a_i$ and $A = \Sigma_i A_i$. The algorithm for this model is illustrated in Fig.2. In this model, there is no problem as in the model by link flows only. That is, this can always produce a unique OD matrix and attain a complete convergence in the iterative calculation for correction of A_i.

In order to investigate error characteristics on OD trip estimates, simulations were also carried out by making variations in R_{ij} and RX_{mn} with the same network as in Fig.3. In this case, a flow on link mn with a certain variance for the true link flow RX_{mn}, is made in the same way as shown before. The reason of considering the variation in RX_{mn} is that traffic count miss and simplification of network representation will cause errors in link flows.

The results of the simulation concerning prediction error in OD trips δ_{OD} and that in link flows δ_X are shown respectively in Fig.9 and Fig.10. Obviously, both of the errors grow with increase in the variances in OD pattern σ_T and that in link flows σ_X. It can be seen, however, that the influence by σ_X on δ_{OD} becomes less as σ_T increases. Namely, when σ_T is large, δ_{OD} is approximately determined by σ_T. Also it can be found that the effect by σ_T on δ_{OD} decreases with the increase in σ_X. As compared with this, it seems that the sensitivity by variation in σ_T on δ_X is approximately equal regardless of increase or decrease in σ_X.

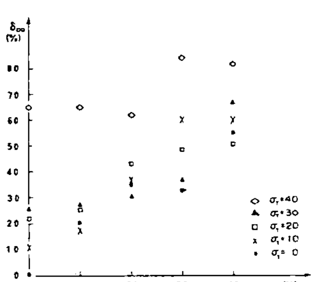


Fig.9 Prediction errors in OD trips.

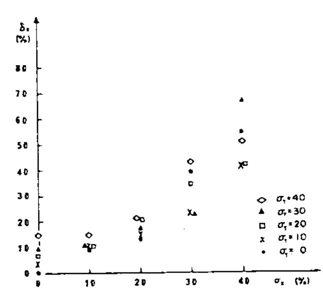


Fig.10 Prediction errors in link flows.

Fig.11 and Fig.12 represent the results of δ_{OD} respectively by variation in σ_X on the assumption $\sigma_T = 0$, and by variation in σ_T on the assumption $\sigma_X = 0$. From this, it can be inferred that an affection by σ_X on δ_{OD} is considerably greater than that by σ_T. But the difference between them would be decreased with increases in the values of σ_T and σ_X.

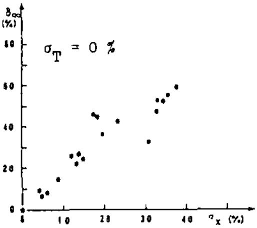


Fig.11 Influence by σ_X on δ_{OD}.

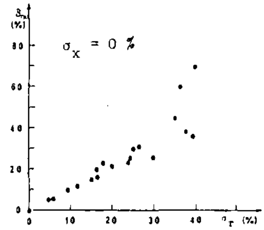


Fig.12 Influence by σ_T on δ_{OD}.

Finally, it must be added that this model converges more quickly than the previous model by link flows only, and this advantage will grow with the increase in the scale of the network.

5. CONCLUDING REMARKS

Two kinds of models for estimating OD matrix by traffic counts were proposed and discussed, which can be applied to a real life network.

With the initial model, an OD matrix can be estimated by obtaining only a set of generation trips of nodes giving a best goodness of fit on link flows for given sets of trip interchange factors and link flow proportions by OD pairs. A sensitivity analysis by simulation on this model revealed that the influence by the variance in OD pattern (or trip interchange factor) on prediction error in OD matrix is considerably great but that by the variance in route choice probability is not significant, in particular when the variance in OD pattern is great. Also the model was found to have a property that the percent error in the estimate becomes less with increase in the number of trips. Namely, the accuracy in the total OD trips is the highest.

But this model has a problem to produce non-unique OD matrix consistent with observed link flows for particular types of network or patterns of route choice behaviour, for example, such as a linear network and a one way loop network. Since a set (or subset) of nodes with non-unique values of generation trips could be easily found through test runs of the model by giving different sets of the initial values, one can give externally proper values to the set of the nodes.

There is another problem in this model that the convergence in the calibration of generation trips can not be necessarily completed, even though the iterative calculation were eternally continued. This is because the calibration is made in terms of the sum of outflows from each node, but not of the respective link flows. But it has been observed that temporal and random perturbations of branching probabilities of link flows at each node can improve effectively the convergence.

In order to overcome the shortcomings of the above model, the known values in advance, which are in general derived from an earlier OD data as stated before. Even though the existing earlier data were spatially aggregated macroscopic one, however, it would not be so much difficult to correct them to match with a real life network under consideration. For instance, assuming that a specific value of trip interchange factor applies to each of a predetermined set of time (or distance) interval, we can determine a separate value for each set of trips occuring within a specific time (or distance) interval. Also it would be possible to obtain a set of generation trip pattern by conducting a simple traffic survey or by using socioeconomic indices.

Equilibrium traffic assignment procedure could be incorporated into the model presented here, but it needs a great amount of computation work. Besides the above simulation has shown that the noise or the variation in route choice probability does not give a vital effect on the OD estimates, and therefore the incorporation of traffic assignment procedure does not always seem necessary if only a prediction of OD matrix is needed.

Entropy maximizing model can calibrate only the OD trips using the observed links but leaves those not included in the observed links unchanged. As against this gravity type model can calibrate the trips between all the OD pairs, whether they are related to the observed links or not. Accordingly it can be said that the number of the observed links for gravity type model is less than for entropy maximizing model.

Finally, a goodness of fit between estimates and observed data is used in the presented models. As compared with this, there is a model using a restriction of agreement between them as seen in mathematical programming technique. Which measure of the closeness should be employed for a practical application is an issue to be further discussed and investigated. If data errors and model specification errors are little, the restriction of agreement may be used, but otherwise, the use of a goodness of fit is considered to be more appropriate, because in such a case an enforcement of the agreement may rather sometimes distort the estimates.

Research on the model proposed here is still under way and must be further investigated for practical use.

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